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Rain Streaks and Snow Removal from Video Streams Using Kalman and Particle Filters

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Abstract: Various weather conditions such as rain and snow will affect the images and video sequence quality. The different parameters of camera captures different dynamics of rain and characterize the photometry of rain. Based on the observation that rain streaks are too small and move too fast to affect optical flow between frames. In the existing model, initial rain map is generated by deducting warped frame from a current frame. Then, the initial rain map is decomposed by basis vector representation and those basis vectors are classified into rain streaks and outliers using support vector machine. The initial rain map is then refined by excluding the outliers. The detected rain map is removed by employing matrix completion algorithm which performs the expectation maximization iterations for the low rank approximation. Instead in the proposed model, the detected rain map is removed by employing a kalman and Particle filtering technique.

Key words: Photometry of rain · Initial rain map · Low rank matrix completion · Support vector machine · Kalman and particle filter

INTRODUCTION

Video capturing devices, such as smart phones and digital cameras are nowadays cheap and popular. Video sequences are often degraded by various weather conditions. Early attempts have been made for haze removal. Dehazing algorithm is applied in the video sequence that enhance the image contrast [11]. The rain and snow are elongated streaks than haze element which hides the colors of object behind. The location of those streaks are randomly distributed within an image and varies dynamically with time [1]. Several deraining algorithm have been proposed, which fails to remove rain streaks clearly [4]-[9]. A low-rank matrix completion technique is carried out to detect the rain streaks in a video sequence. The initial rain map is formed by subtracting warped frame from a current frame. To represent the initial rain map basis vector representation is applied, which dichotomize the basis vectors into rain streaks and outliers using the support vector machine. By excluding the outliers the rain map is refined and the rain streaks are then detected. Finally the detected rain streaks are removed using Kalman and Particle filter.

Existing Model: Wan-Joo Park and Kwae-Hi Lee. explained the recursive data processing and the intensity value of each pixel. This method needs the periodic reset. If unsuitable estimated mean value is determined because of heavy noise, henceforth cleanly capture scene has little weight effect for estimated mean value. Accordingly reset the weighted value between estimated intensity and new captured one. This proposed system is not applicable in moving camera scenes. Li Xu Jiaya Jia and Yasuyuki Matsushita explained a proposed algorithm which is used to reduces the reliance of the flow estimates on their initial values propagated from the coarser level and enables recovering many motion details in each scale. The contribution of this paper also includes adaption of the objective function and development of a new optimization procedure. The effectiveness of this method is borne out by experiments for both large- and small-displacement optical flow estimation. It might not perform well enough when a small region is entirely textureless. Li-Wei Kang, Chia-Wen Lin and Yu-Hsiang Fu explained a single-image-based rain removal, in this proposed algorithm it decompose an image into the low- and high-frequency (HF) parts using a bilateral filter. The HF part is then

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decomposed into a "rain component" and a "non-rain component" by performing dictionary learning and sparse coding. As result the rain component is removed successfully. The disadvantage of this proposed system the dictionary learning and sparse coding represents most of the execution time. The number of patches of dictionary learning and sparse coding will be significantly fewer than whole image learning. Jie chen and Lap-puichau explains a motion segmentation of dynamic scene. After applying photometric and chromatic constraints for rain detection, rain removal filters are applied on pixels such that the dynamic property as well as motion occlusion clue are considered both spatial and temporal informations are then adaptively exploited during rain pixel recovery.

The rain streaks appears randomly and each streak occupies a relatively small area in a frame and moves fast between consecutive frames. When a rain passes across the pixel value become brighter than its original color [5]. Thus, the pixels which has a larger value in a current frame than in adjacent frame is considered as rainy pixels [6]. Sometimes, this approach may lead to mismatches with the pixel value. To compensate these mismatches warping of previous frame into current frame is processed. By this initial rain map is obtained which is decomposed into basis vectors. Rain streaks are basically in elliptical shape. Initial rain map are refined by excluding the outliers. An overview of the existing model is explained in the fig.1 below.

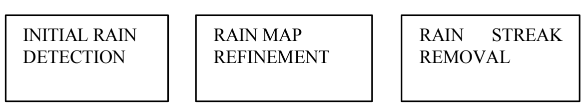

Fig. 1: An overview of the existing model: An initial rain map from an image frame, is obtained which is then refined based on vector representation. Finally, we reconstruct a rain-free frame by exploiting the information in adjacent frame.

The rainy free pixel values should be smaller than the rainy pixel value. So constraint matrix completion technique, to solve optimization problem Expectation Maximization(EM) algorithm is used that converges after 70 iterations. Post processing is carried out even after rain streak removal that remove thin rain streaks which are not detected in rain map.

Proposed Model: In the proposed model, Preprocessing is carried out to enhance the data images prior to the computational processing. It removes low-frequency background noise and reflections. It also normalize the intensity of the individual particles and used for masking a particular portion in the frame. A low-rank matrix completion technique [12] is used to detect the rain streaks and a initial rain map is generated, which is then decomposed into basis vector representation. The classifier is applied to convert those basis vectors into valid rain streaks and outliers. Images and video are represented in pixels with noise thus to remove noise filtering technique is used. Kalman filter is used to increase accuracy of output image than other filters. It uses a series of measurements which is observed over time. Particle filter is used to solve complex optimization problems. The proposed system involves five modules.

- Preprocessing.
- Initial rain detection.
- Rain map refinement.
- Rain streaks removal.
- Kalman and Particle filter.

Preprocessing: A video with rain streaks is considered as input which is then converted into frames then those frames undergoes preprocessing. Preprocessing is carried out to enhance the data images prior to computational processing. It removes low-frequency background noise and reflection. It normalize the intensity of the individual particle and also used for masking a particular portion in the frame. Preprocessing is mainly done to convert colored (RGB) images to grayscale image which is explain in fig.2.

Initial Rain Detection: The rain streaks appear randomly and each streaks occupies a relatively small area in a frame and moves fast between consecutive frames. Also, when a rain streaks passes across a pixel, the pixel value becomes brighter than its original color. Hence rainy pixels are detected if the pixel had a larger value in a current frame than in adjacent frames [6]. This approach, may lead to mismatches so to compensate previous frame is warped into current frame by estimating the optical flow estimation. A initial rain map is generated from the difference between current frame and warped frame. Initial rain map is detected from preprocessed image in fig.3. The preprocessed image is converts the original image to grayscale image, then the rain streaks is detected from the image.

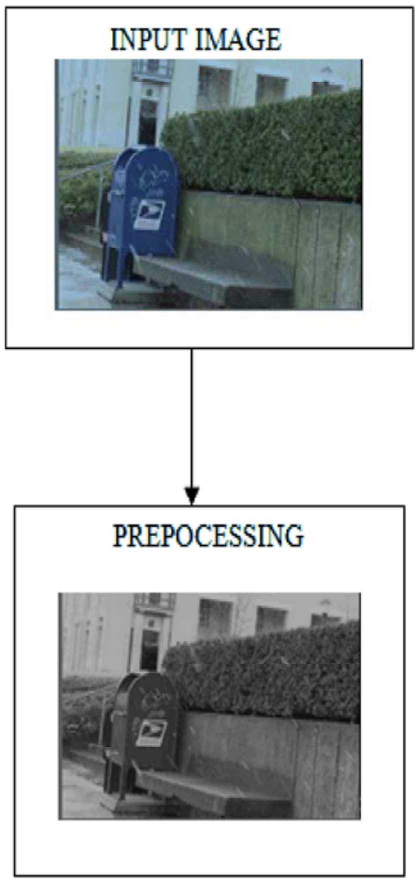

Fig. 2: Preprocessing is carried out with the given input image that enhance data images prior to the computational process

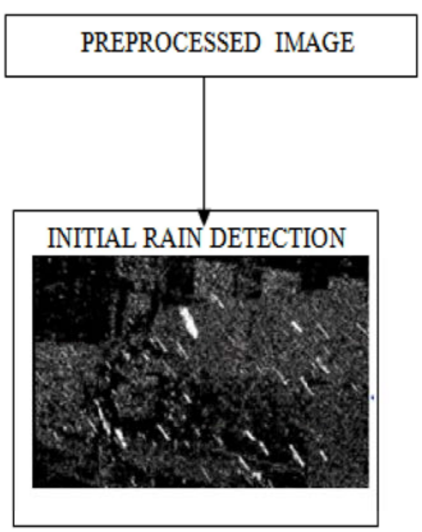

Fig. 3: An initial rain streaks are detected after preprocessing the input image

Rain Map Refinement: The Initial Rain Map which is generated once rain streaks are detected is then decomposed into basis vector representation. It perform simple thresholding with various choices of threshold. In general, if the threshold value is decreased, the outliers are falsely detected as rain streaks. On the contrary, if the threshold value is increased, this mislead is reduced but sometimes valid rain streaks are missed. Moreover, outliers often overlap with valid rain streaks. Therefore, to detect valid rain streaks initial rain map is refined before thresholding which is shown in the fig.3. To refine an initial rain map, directional property of rain streaks are exploited.

Rain streaks tend to have elliptical shapes, whose major axes deviates little from the vertical direction. By comparing the horizontal components with the vertical components of detected ellipses valid outliers are found. However, eliminating elliptical regions with large horizontal components may miss actual rainy pixels, since rain streaks and outliers occur simultaneously and may overlap each other. The morphological component analysis (MCA) decomposes a given signal into basis vector representation and then reconstructs the signal by employing selected basis vectors only. Note that this approach was adopted in [8] and [9] to decompose an edge map, which represents high frequency information in an image into rain and rain-free components.

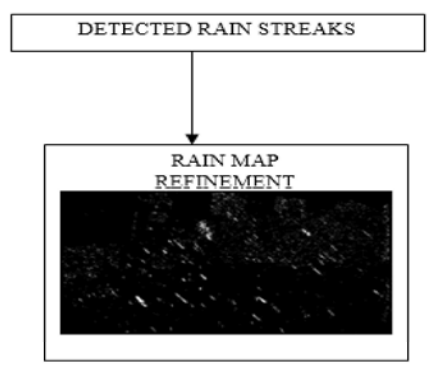

Fig. 4: A rain map refinement is carried out with vector representation and support vector machine

Rain Streak Removal: In rain streaks removal module the rainy pixels are replaced using low-rank matrix completion [12]. It performs Expectation Maximization (EM) iteration for low-rank approximation. The current frame (Ik) is partitioned into disjoint blocks. For each block b, I most similar blocks from each of the four adjacent frames:Ik-2, Ik-1,Ik+1,Ik+2 is searched. But similar blocks from current frame is not found because similar blocks in the current frame tend to be selected near the given block band affected by the same rain streaks, which degrade the deraining performance. To measure the similarity between two blocks, the sum of the squared differences between rain-free pixels is computed.

Kalman and Particle Filter: Images and videos are represented in pixel with noise. To remove those noise, filtering technique is used. Two filters are used to remove noise in the image or video they are Kalman and Particle filter to improve quality and accuracy. Kalman filter is used to increase the accuracy of output image than the other filters output. It uses a series of measurements observed over time. It contains statistical noise and other inaccuracies. It produce estimates of unknown variables which tend to be more precise than those filters based on a single measurement alone. Particle filter is used to solve filtering problem. It is mainly used to solve complex optimization problems.

WORK FLOW DIAGRAM

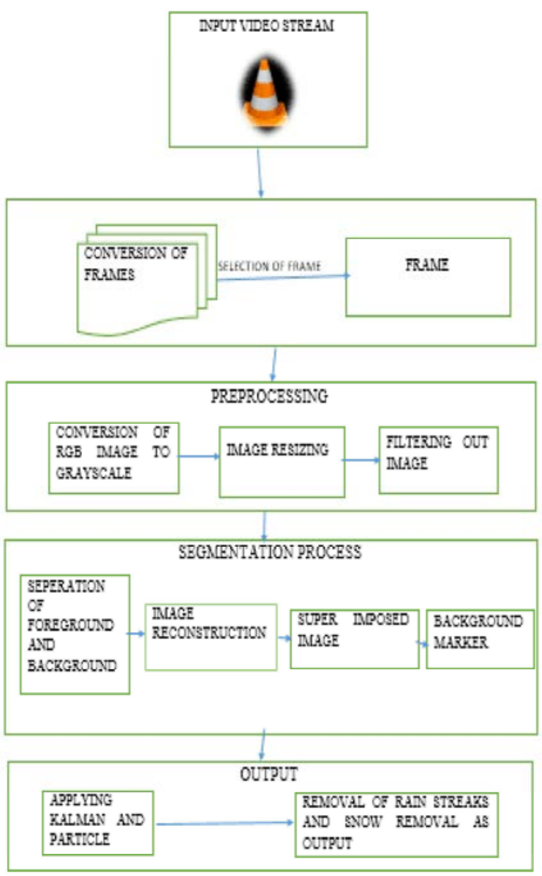

Figure 5 An overview of proposed model: A input image is preprocessed to convert it into grayscale image without noise, then initial rain streaks are detected is refined by vector representation. Finally, the detected rain streaks are removed using Kalman and Particle filters.

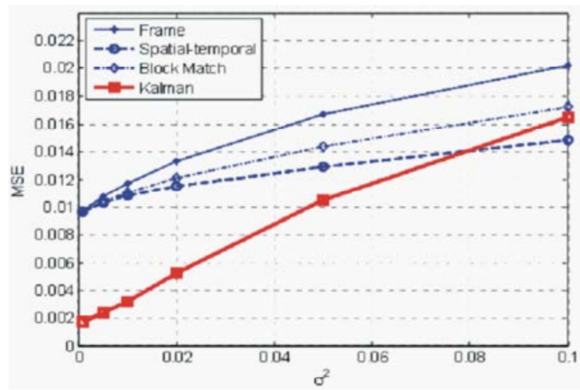

Fig. 6: Comparing MSE values of different types of filter

Experimental Analysis: The performance of proposed algorithm on video sequences is evaluated based on calculating the Mean Squared error (MSE) values of different types of filters. The existing algorithm is implemented in Matlab without code optimization which is then overcome by the proposed algorithm. High complexity could be reduced by approximating the vector representation and block matching algorithm in the proposed model. Kalman filter is used to increase the accuracy of the output image than the existing model. Particle filter is used to solve complex optimization.

CONCLUSION

In this paper, the proposed model defines rain streaks and snow removal from video using kalman and particle filter which obtains an initial rain map by comparing the warped frame with a current frame. It then refines the initial rain map by removing outliers. Finally, the proposed model fills the rainy pixels using low rank detection. Then kalman and particle filter is used to reduce the noise and remove tiny particles from the image. The experimental results from the proposed model removes the rain streaks and snow from video using kalman and particle filter to achieves more accuracy than other filters. The clarity of the image is increased by using kalman filter. The future work is to reduce the execution time.

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